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Heliyon 10 (2024) e35048

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

# A data-driven Bayesian network of management and organizational factors for human reliability analysis in the process industry

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ARTICLE INFO

*Keywords:*
Process safety
Organizational factors
Socio-technical systems
Causal Bayesian network

ABSTRACT

According to historical statistical data, management and organizational factors (MOFs) contribute more to process accidents than technique factors. Under the umbrella of socio-tech system theory, human reliability analysis (HRA) has become a critical part of systemic probability risk analysis. In many HRA techniques, MOFs are among the performance shaping factors (PSFs). However, the interactions and causality of MOFs to human errors are still difficult to quantify and lack validation. To fill these gaps, a framework is proposed, considering data source selection, CBN construction algorithm comparison, and results validation. The case study employed the open access eMARS database as a data source. The optimized hybrid structure learning algorithm and Bayesian criteria parameter learning algorithm are employed to build a Causal Bayesian Network (CBN) of (MOFs) that lead to human error. The proposed kernel CBN is validated through prediction accuracy and sensitivity analysis. For theoretical contribution, the validated kernel BN could generally serve as the heart part of more specific CBNs as a basis for future works. For practical applications, an application shows the model's ability to quantify the contribution of MOFs to system reliability. The results show that human-machine interacting system reliability is most sensitive to organizational factors such as adequate training and procedures.

## 1. Introduction

Process accidents have significant potential to harm lives, properties, and the environment due to the potential loss of containment of large amounts of hazardous material and the related consequences. According to the online Major Accident Reporting System (eMARS) database, around 43.8 % of hazardous material-related accidents were related to human and organizational factors [1]. The Center for Chemical Process Safety (CCPS) and the Energy Institute addressed these factors in bow ties, which could significantly improve process safety [2]. The process industry plants can be viewed as socio-technical systems, where the complexity arises from hard and soft components and their interactions towards potential accidents. As technology develops to keep enhancing the hard component's reliability, the soft component's reliability is catching more attention from academic and practical perspectives.

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https://doi.org/10.1016/j.heliyon.2024.e35048
Received 16 April 2024; Received in revised form 11 July 2024; Accepted 22 July 2024
Available online 26 July 2024
2405-8440/

Human reliability analysis (HRA) is an important tool for supporting process safety management as part of systemic probability risk analysis. HRA is an evolving discipline that employs qualitative and quantitative methods to evaluate and mitigate the probability of human error. In the theoretical background, human reliability refers to the likelihood of successful human performance within defined task parameters and timeframes. On the other hand, human error encompasses the various factors influencing human reliability across diverse conditions and environments [3]. More than 50 HRA methods have been proposed since the 1980s to estimate the probability of human errors, from the Technique for Human Error Rate Prediction (THERP) [4] to the general methodology of an integrated human event analysis system (IDHEAS-G) [5]. Although some attempts begin to extend HRA with cognitive models like situation awareness and mental workload, they can be objectively measured by physiological signals [6]. Their result quality highly relies on the experiment design. Their findings are still at the correlation level other than causality analysis, for ignoring multi-confounders.

In a more traditional approach, the quantification of MOFs in terms of performance shaping factors (PSFs), performance influencing factors (PIFs), and common performance conditions (CPCs) still rely on expert judgment. These factors indicate aspects of context that affect human performance [7]. In this research, PSFs will be used to refer to them all. In the qualitative phase of HRA, PSFs are used to analyze the human error mechanism. In contrast, the quantitative phase employs PSFs to estimate multipliers to modify the nominal human error probability (HEP).

Great effort has been spent to build a standard set of PSFs with definitions and indicators. Relevant pieces of literature are summarized in Table A.1 (in Annex A). However, few researchers validated PSFs and their causal relationship with evidence data considering their interactions. When it comes to the quantitative part, traditionally, these methods must assume PSFs are independent or simplify the factor interactions as scale levels that are mutually dependent, like low, middle, and high, which is usually not the case.

Bayesian networks (BN) were proposed to perform prediction and "abduction" inference in artificial intelligence (AI) systems for their ability to combine observations and prior information and to update when new observations are available. However, the advantages of modeling causality make them ubiquity, with the concepts of interventions and counterfactuals [8]. These metrics make the Causal Bayesian Network (CBN) a visualized mathematical vehicle representing the causality relationship between PSFs and human error.

Groth & Mosleh (2012) developed a data-deriving method based on correlation analysis of pairwise factors other than the causality learning algorithm [9]. Musharraf et al. (2014) proposed a data collection methodology utilizing the virtual environment to simulate emergency scenarios [10]. A BN was set up with three independent factors, visibility, complexity, and training, based on author group design, and 43 data samples were collected in the experiment. Wang Yanchun et al. (2019) code the database themselves and classify unsafe and irregular operations according to their experience to build up a BN on unsafe acts during hot work [11]. Morais et al. (2022) proposed a methodology using the credal network to deal with missing data and analyzed human reliability [12]. However, the structure of this credal network in the case study was defined also by the author's experience and knowledge. To reduce the influence of subjective bias, Liu et al. (2022) a BBN framework was proposed to explore the PSF clusters based on the Exploratory Factor Analysis (EFA) technique [13]. However, this approach did not explain how the PSFs interact like confounders. Mkrtchyan et al. [14] criticized most papers they reviewed applying the Bayesian belief network (BBN) to HRA but did not thoroughly discuss the BBN building phase. Previous researchers used either only the literature foundation or experts' judgment to build the BN structure or set the conditional probability table (CPT), which will introduce subjective bias, cost much time and human resources, and cannot be validated in a clear way.

Thanks to the development of machine learning technology, this study employs data-driven learning strategies to build a Bayesian network to overcome the above-described problems. For the rare evidence data for HRA, other than building a complete BN, this research aims at training a kernel BN model based on prior knowledge and general accident report data and then utilizing the specialized plant-level or experiment-level data to update the kernel BN to a more detailed network to fit the special scenarios. The main contributions of this research are:

(1) This research proposed a robust CBN of MOFs, considering the causality interactions between MOFs, other than correlation analysis ignoring confounders.
(2) The accident reports database containing expert knowledge was chosen as a data source to support the CBN structure and parameter learning and validation.
(3) The hybrid method max-min hill climbing (MMHC) machine learning algorithm is employed in mining causality based on the accident reports data, the learned CBN performance was compared with other benchmark algorithm results. The learned model was validated by prediction accuracy and sensitivity analysis. The virtual evidence from the literature is used to solve the data unbalance problem.
(4) A case study of the spherical tank polishing process is employed to test the sensitivity of the system's reliability to MOFs. The discrete event simulation is built to include all the combinations of the MOFs' states.

The paper is organized as follows. Section 2 describes the theoretical background. Section 3 demonstrates the methodology. Section 4 applies this methodology in the Bayesian network building based on the eMARS dataset. Section 5 Applies this Bayesian network in the case of the spherical tank inspection process to analyze the contribution of MOFs to the system reliability. Section 6 shows the results and discussion. Section 7 concludes this paper.

## 2. Theoretical backgrounds

### 2.1. Holistic framework

The framework of this study is shown in Fig. 1. In the first phase, the causality model is built as a CBN of MOFs based on empirical data from accident reports. Unlike most machine learning data analysis methods that are black boxes, the causality model contains more information about changes and interventions and the relationship among variables [15]. This means the causality model can disclose the causality influence mechanism, which is that the decision-makers are more concerned about rather than a number representing human error probability. BN is one of the most advanced theories with widespread recognition in discovering causality [16]. Causal Bayesian Networks (CBNs) enable decision-makers to simulate the effect of interventions and counterfactual reasoning. This likely results in more effective measures to reduce human errors and implantation prevention policies and human error reduction and prevention policies. The second phase applies the Bayesian inference and the causality model to calculate the range of human failure rates considering the contribution of critical MOFs. The human-machine system is then simulated to quantify the sensitivity of system reliability to the critical MOFs through a reliability block diagram approach.

### 2.2. Data quality

A big concern of the data-driven approach is data quality. With digital technical development, data on technical failure factors can be obtained based on accident simulations in a virtual environment. The evidence data on the failure state of MOFs can only be gained from real records and is influenced by human judgment. Unlike manual code or questionnaire survey data, which often reflect opinions from the limited experience of coders or responders, the open access accident report database is a good data source. They descend from formal investigation procedures based on the objective study and analysis of the accidents from committees of multi-discipline parties, government, domain experts, and factory administrative representatives. One shortcoming of the accident report data is that it is unbalanced. Since the data sample referred to an accident, the resulting probability of human error is higher than the reality values. To solve this problem, the SPAR-H nominal value of the human error of action as 0.001 is adopted as the virtual evidence to update the data [17].

## 3. Methodology

In this study, CBN automatically learns using the “Bnlearn” package in R based on the accident reports dataset and visualized with GeNle software. “Bnlearn” provides various machine-learning algorithms for BN structure construction and parameter estimate [18]. GeNle for BN visualization and calculate the impact strength and conditional probabilities range. The methodology is shown in Fig. 2.

### 3.1. Data collection and pre-processing

In this research, the accident reports database is chosen as a data source. Identifying the organizational, human, and technical causative factors is a critical part of accident investigation, which will be performed by a safety expert committee. In the accident reports, relevant organizational factors were investigated by safety experts and validated with record evidence such as training records. In this way, the data extracted from officially published accident reports could serve as evidence data to support Bayesian Network learning.

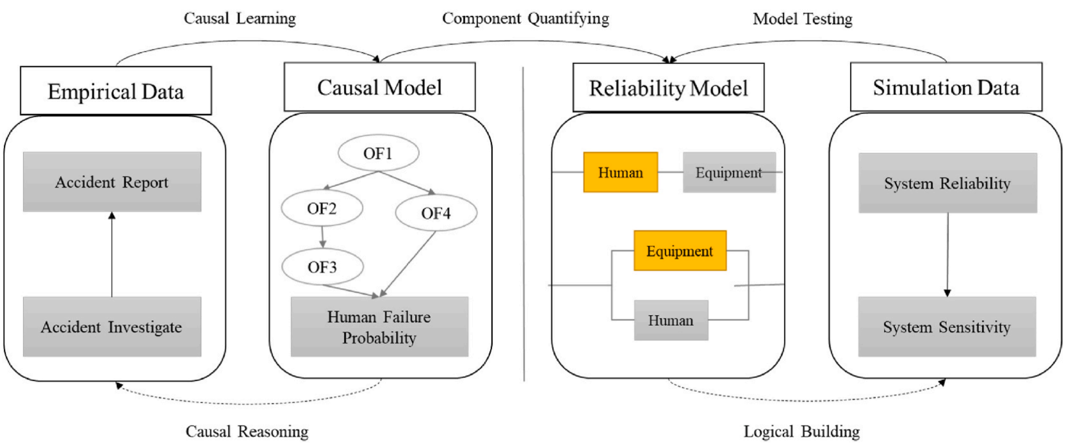


**Fig. 1.** The holistic framework.

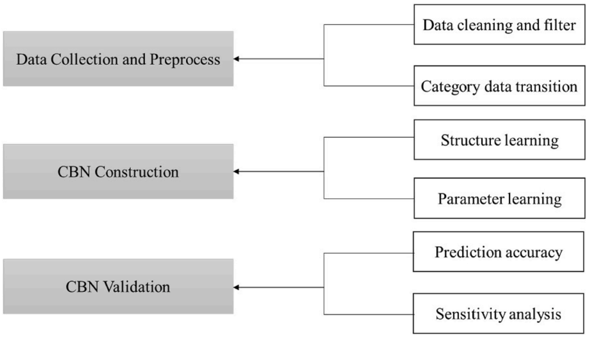


**Fig. 2.** The methodology.

### 3.2. CBN construction

#### 3.2.1. Structure learning

Three main BN structure learning algorithm categories are constraint-based (CB), score-and-search (SS), and the hybrid method. The CB method is mainly based on statistical tests to identify the conditional independence (CI) relations of variables from data. A detailed introduction of the structure learning algorithm could be referred to in the relevant review [19].

This study employs the hybrid max-min hill climbing (MMHC) method to build the BN structure. This research codes each MOF state as a binary value (0 or 1 for the "Success" or "Fail" state), so the node of BN has the Binomial distribution, which can be viewed as a particular form of the multinomial distribution. Based on this assumption, the stable-PC algorithm with a Chi-square as a CI test method is chosen firstly, with a p-value of 0.05, to reconstruct a Bayesian network's skeleton and then perform a Bayesian Dirichlet score-based hill-climbing search to orient the edges.

In the case of a limited number of samples, it is necessary to use the total dataset wisely. The bootstrap resampling considers the sample set as the population and obtains subsamples from it. Model averaging is a technique that utilizes bootstrap data to build robust edges with a statistic occurrence rate higher than the threshold values. The arc direction threshold value is set to 0.5 to determine the direction. Considering the trade-off between keeping more information and being more robust, the arc strength threshold values are set to 0.5 at the beginning and increase to 0.85 with a step of 0.05 to explore the balance threshold.

#### 3.2.2. Parameter learning

When the structure is fixed, BN parameter learning allows the conditional distribution of every variable to be identified through the sample data. The parameter of nodes in BN can be learned from a sample dataset of cases. When the data is complete with no missing data, the prevalent methods are maximal likelihood evaluation (MLE) and Bayesian evaluation. The MLE views the parameter as an unknown constant, while the Bayesian parameter estimation views the parameter as a random variable. The MLE often leads to overfitting and is sensitive to small sample sizes. This study thus employs the Bayesian Dirichlet parameter estimation approach. The MOFs are coded as binary variables and have a Binomial distribution, a particular form of the multinomial distribution.

### 3.3. CBN validation

Cross-validation is a standard way to obtain unbiased estimates of a model's goodness of fit. By comparing such estimates for different learning strategies (different combinations of learning algorithms, fitting techniques and the respective parameters) we can choose the optimal one for the data at hand in a principled way. 10-fold cross-validation is commonly used [20], and that parameter will be used in this research.

Sensitivity analysis [21] is a technique that can help validate the probability parameters of a Bayesian network. This is done by investigating the effect of small changes in the model's numerical parameters (i.e., prior and conditional probabilities) on the output parameters (e.g., posterior probabilities). Kjaerulff and van der Gaag [22] presented a method that requires a single outward propagation in a junction tree to establish the coefficients in the functions for all possible parameters. Given a set of target nodes, the algorithm efficiently calculates a complete set of derivatives of the posterior probability distributions over the target nodes over each of the numerical parameters of the Bayesian network. These derivatives indicate the importance of network numerical parameters' precision for calculating the targets' posterior probabilities.

## 4. Construction of an eMARS data-driven Bayesian network

### 4.1. Data collection and pre-processing

The eMARS dataset includes decisions on the causative factors of the accident, which includes the organizational factors type. This means the eMARS dataset gives the types of MOFs and the state of each MOF for every accident record. In addition, the eMARS dataset is open access, which makes it possible for other researchers to verify it conveniently. So, the eMARS accident database has been chosen as the data source for this research.

The eMARS dataset[1] is an open-access database maintained by the Major Accident Hazards Bureau of the European Commission's Joint Research Centre. The dataset selected in this study includes accidents involving hazardous material release [23]. The industry domain is limited to the process industry. The industry type has been chosen according to Table 1. From data across 40 years from 1980 to 2022, 893 cases are extracted.

In the database, the accidents are characterized through 73 columns, six of which have been considered in this study: Accident ID, Plant/Equipment Causative Factor Type, and Human and Organizational Causative Factor Type. External Causes are excluded from this research. Then, Plant/Equipment Causative Factor Type, Human, Organizational Causative Factor Type, and External have been coded into binary factors as Table 2 shows, where 1 represents fail, and 0 represents success. The factors having no clear definition, like "others", and factors with less than ten samples were excluded directly.

### 4.2. CBN construction

#### 4.2.1. Structure learning

Twenty-three factors were analyzed using the bootstrap samples method for a robust structure. Broom et al. (2012) explored the space of model-averaging strategies with limited data and suggested that 2500 bootstrap samples are needed for robust estimation [24]. Therefore, the bootstrap samples were adopted to resample the data 2500 times, learning one structure from each sample and then checking the frequency of one arc occurrence rate. The first-round result CBN1 of the structure learning is shown in Fig. 3. Based on CBN1, the connected organizational factors and human error-related factors were kept, with eight variables (O9, O1, O8, O5, O13, H2, O11, H4), and the second-round structure learning was performed with 2500 bootstrap samples.

Excluding the separated part of CBN1, the CBN2 could be obtained. After calculating the cumulative distribution function for the arc strength, the threshold of the CDF is 0.48, as Fig. 4 shows. The higher arc strength value means higher stability. This research aims to find a robust kernel network of the organizational factors leading to human errors. Therefore, the arc strength threshold was set to start at 0.5 to 0.9 and increase with a step value of 0.05. The results are shown in Fig. 5. However, with the threshold of 0.9, one human error factor type (H4) will be separated from the target Bayesian Network, which is not a complete solution. Therefore, the CBN4 was selected, with a threshold of up to 0.85. At the same time, the "BDe" score method aims at searching for the set of equivalence classes of Bayesian network structures [25]. For the causal direction of O13 (Training) and O8 (Procedure), according to the time sequence, it can be inferred that the direction should go from O8 to O13. In this way, the final structure could be gained, as Fig. 7 shows.

#### 4.2.2. Parameters estimation

Then, the dataset is split into a 0.75 train set and a 0.25 test set. The node's parameters were estimated using the Bayesian score based on train set data, obtaining the conditional probability table (CPT). An example of CPT is shown in Table 3.

### 4.3. CBN validation

10-fold cross-validation is employed to compare our CBN model with other benchmark algorithms: "TABU, HC, and H2PC," as discussed in the literature [19]. The results, as shown in Fig. 6, show that our model overwhelmed the other three algorithm results, having much lower mean and variation in terms of Log-Likelihood Loss.

50 runs of 10-fold cross-validation have been performed to validate the model learning strategy and measure the predictive accuracy for human error variables (H2 and H4), as shown in Table 4.

### 4.4. Visualization of the Bayesian network and sensitivity analysis

Procedures and training are two directly influential factors in Operator Error. At the same time, supervision is a directly influential factor in Willful Violations. The GeNle Academic Software is applied to visualize the Bayesian network and analyze the sensitivity. Since the data sample referred to an accident, the resulting probability of human error is higher than the literature reference values. Therefore, our model gives back a value of 0.19. To solve this problem, the SPAR-H nominal value of the human error of action as 0.001 is adopted as the virtual evidence to update the data [17]. According to the accident dataset, the operator error and willful violation ratio is 9:1. Therefore, the operator error probability can be updated with set virtual evidence as the prior failure rate is 0.0009 for operator error and 0.0001 for willful violations rate. After the update, the whole BN is shown in Fig. 7. The sensitivity analysis of the Bayesian network is shown in Fig. 8, where the redder color means the variables are more sensitive, and then O1 (Design) is excluded, as it does not contribute to the human error failure rate as the sensitivity analysis results show. Then, the final kernel Bayesian network is shown in Fig. 9. Based on the updated BN model, the range of HEP under the organizational evidence factor can be gained, as Table 5 shows.

The learned CBN model comprises five organizational variables: Design, Process Analysis, Procedures, Training, and Supervision. The data from the accident report only have two states of these factors; the binary states are kept. According to the literature (in Annex

[1] accessible at https://emars.jrc.ec.europa.eu/en/emars/accident/search.Retrieved November 17, 2022.

**Table 1**
The list of process industry type.

| | |
|---|---|
| 1. | Chemical installations (include ammonia, carbon oxides, chlorine, fluorine or hydrogen fluoride, industrial gases, inorganic acids, nitrogen oxides, other fine chemicals, sulphur oxides, oleum) |
| 2. | General chemicals manufacture |
| 3. | LPG production, bottling and bulk distribution |
| 4. | Manufacture of food products and beverages |
| 5. | Manufacture of glass |
| 6. | Petrochemical/oil Refineries |
| 7. | Plastic and rubber manufacture |
| 8. | Processing of ferrous metals (foundries, smelting, etc.) |
| 9. | Processing of metals |
| 10. | Processing of metals using electrolytic or chemical processes |
| 11. | Processing of non-ferrous metals (foundries, smelting, etc.) |
| 12. | Production and manufacturing of pulp and paper |
| 13. | Production and storage of fertilizers |
| 14. | Production and storage of fireworks |
| 15. | Production and storage of pesticides, biocides, fungicides |
| 16. | Production of basic organic chemicals |
| 17. | Production of pharmaceuticals |
| 18. | Production, destruction, and storage of explosives |

**Table 2**
The representation of the factors.

| Organizational Factors | | Human Factors | |
|---|---|---|---|
| O1 | design of plant/equipment/system | H1 | malicious intervention (excluded) |
| O2 | installation (excluded) | H2 | operator error |
| O3 | isolation of equipment/system | H3 | operator health (includes ailments, intoxication, death, etc.) (excluded) |
| O4 | maintenance/repair | H4 | willful disobedience/failure to carry out duties. |
| O5 | management attitude problem | H5 | other (excluded) |
| O6 | management organization inadequate | | |
| O7 | manufacture/construction | **Plant/Equipment Factors** | |
| O8 | organized procedures | E1 | blockage |
| O9 | process analysis | E2 | component/machinery failure/malfunction |
| O10 | staffing | E3 | corrosion/fatigue |
| O11 | supervision | P1 | unexpected reaction/phase-transition |
| O12 | testing/inspecting/recording | P2 | electrostatic accumulation |
| O13 | training/instruction | E4 | instrument/control/monitoring-device |
| O14 | user-unfriendliness (apparatus, system, etc.) | P3 | runaway reaction |
| O15 | others (excluded) | P4 | loss of process control |
| | | E5 | vessel/container/containment-equipment failure |
| | | E6 | others (excluded) |

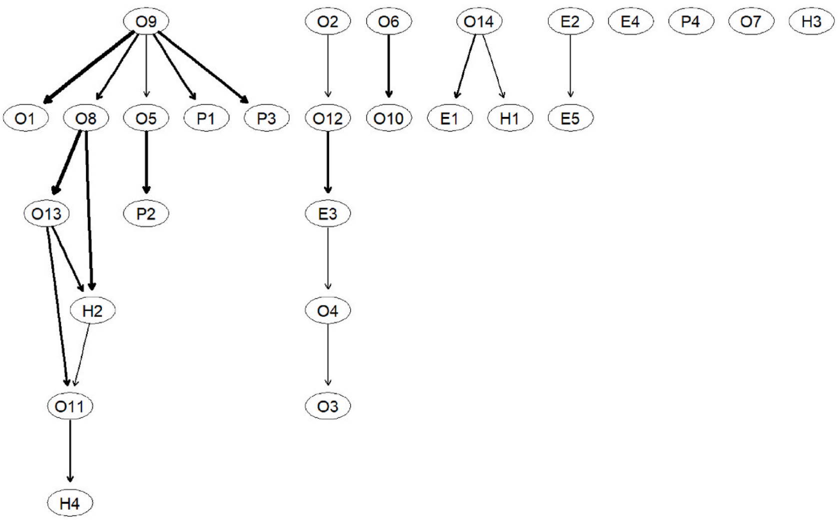


**Fig. 3.** CBN1 based on Bootstrap MMHC structure learning (network score = "BDe", CI test = "×2", p-value = 0.05, arc direction thresholds = 0.5).

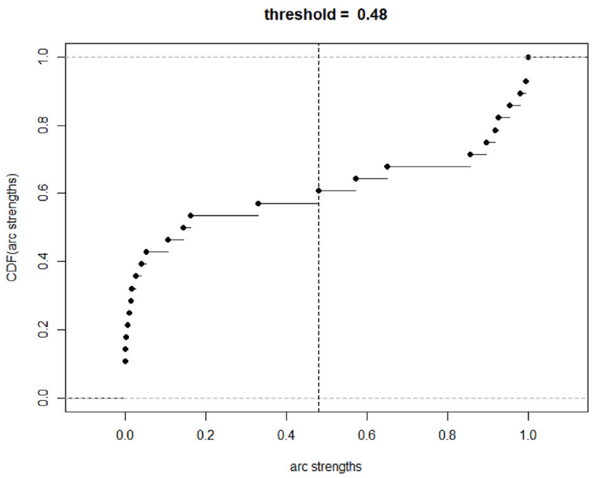


**Fig. 4.** CDF for arc strengths of CBN2.

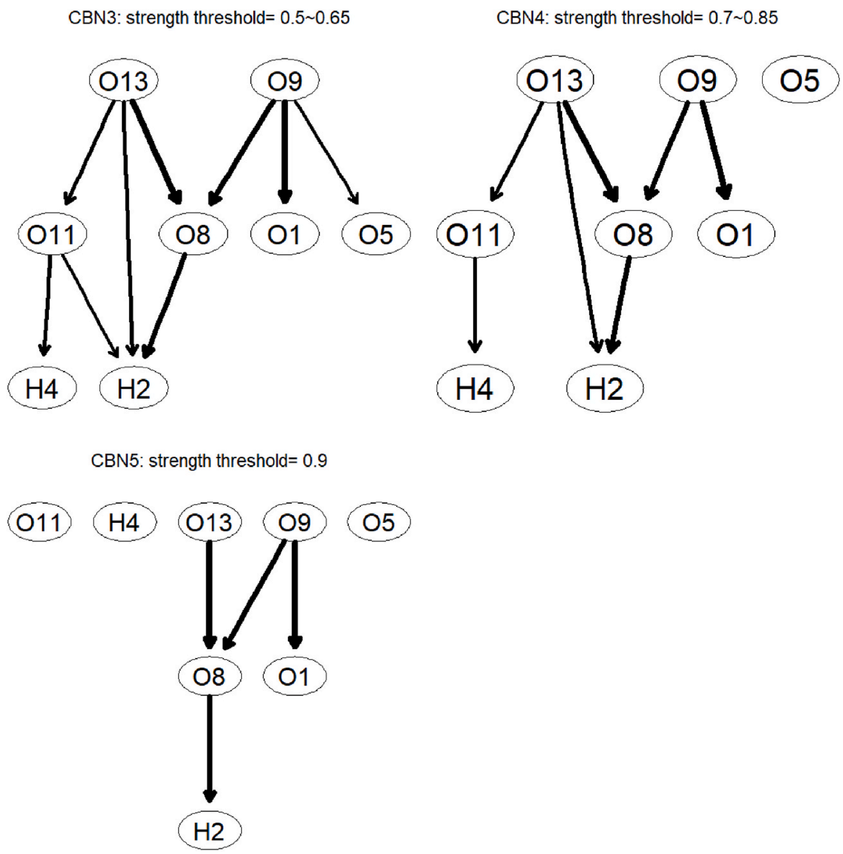


**Fig. 5.** CBN3~CBN6 changes with strength threshold.

A.1)., the success criteria for these five factors are set up to facilitate the implementation.

#### 4.4.1. Success design

- Process equipment compatibility of materials with products
- Safety instrumented system satisfied the standards
- Ergonomically support easy installation, inspection, and maintenance

**Table 3**
The conditional probability for the variable procedure.

| | Training | | | |
|---|---|---|---|---|
| | Success | | Fail | |
| | Procedure | | Procedure | |
| Operator Error | Success | Fail | Success | Fail |
| Success | 0.8911626 | 0.6379310 | 0.5551724 | 0.3976109 |
| Fail | 0.1088374 | 0.3620690 | 0.4448276 | 0.6023891 |

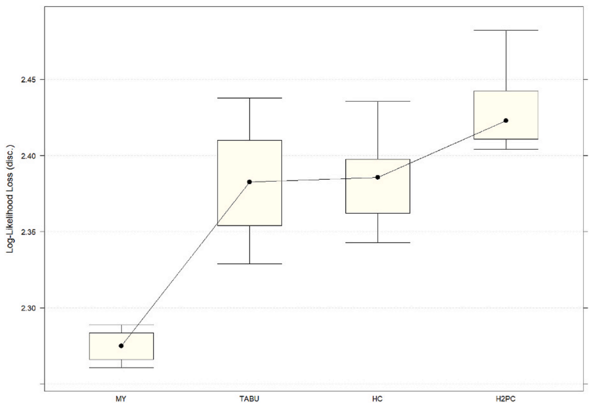


**Fig. 6.** Performance comparison of our CBN with other three structure learning algorithms results.

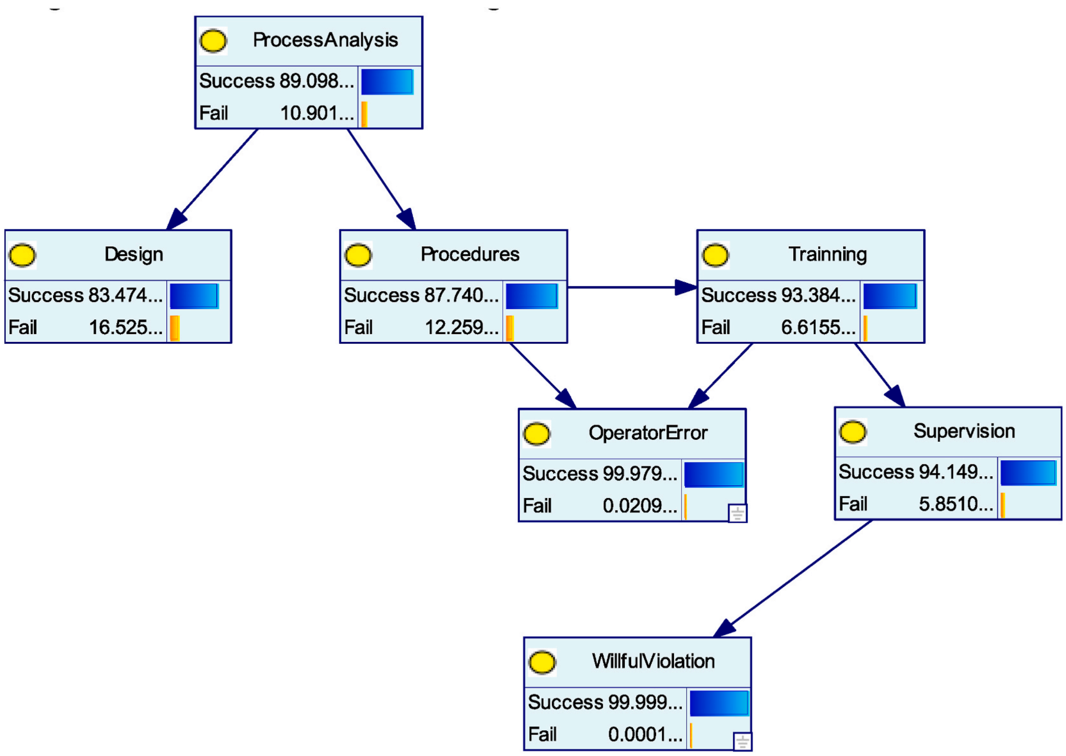


**Fig. 7.** BN structure of organizational factors to human error.

**Table 4**
Predictor loss.

| Human error variables | H2 | H4 |
|---|---|---|
| Predictor loss | 0.174 | 0.016 |

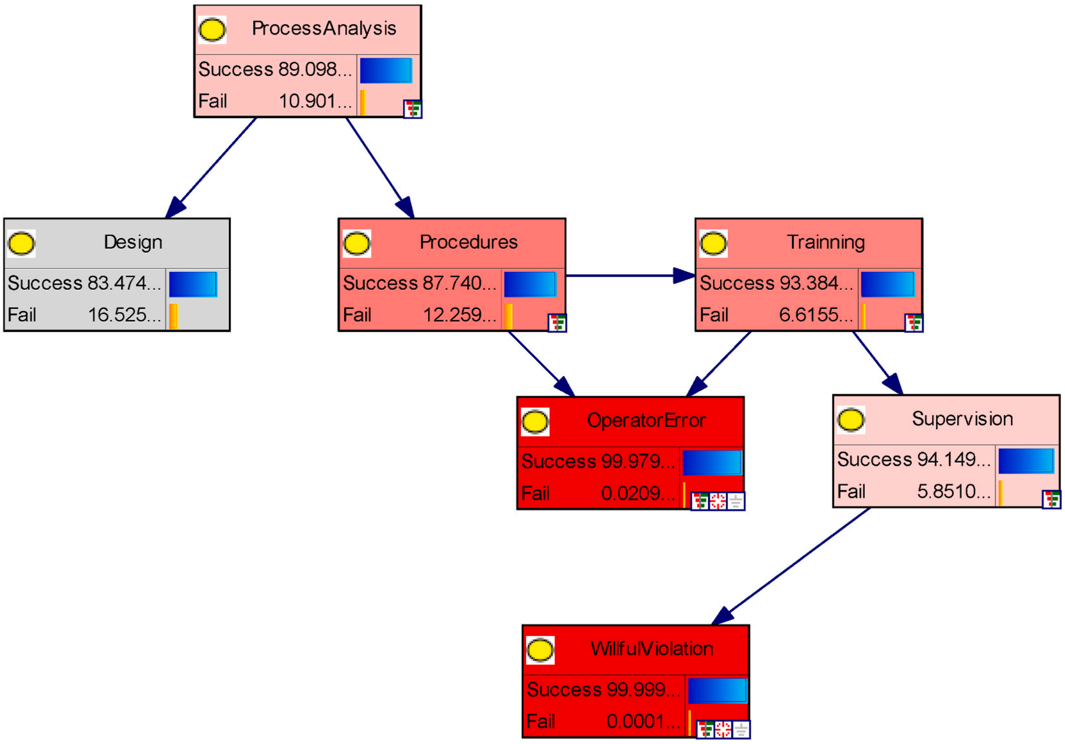


**Fig. 8.** The sensitivity analysis when target set as operator error and willful violation.

### *4.4.2. Success procedure, guidelines, and instructions*

- Availability of procedures
- Specifying measurable requirements about what to achieve and how to follow these should lead to the success of important human actions
- Kept up to date and reviewed regularly
- Including emergency plans and actions

### *4.4.3. Success training*

- Training courses and programs cover all critical safety aspects
- Various training forms, including course and field or virtual simulated practice
- More than six months of training time before becoming a formal worker
- Safety-critical operators have enough knowledge and skills

### *4.4.4. Success direct supervision*

- Perform preparation supervision
- Perform during work supervision

### *4.4.5. Success process safety risk analysis*

- Performed before formal operation and before process change
- Performed by process experts and staff familiar with the process

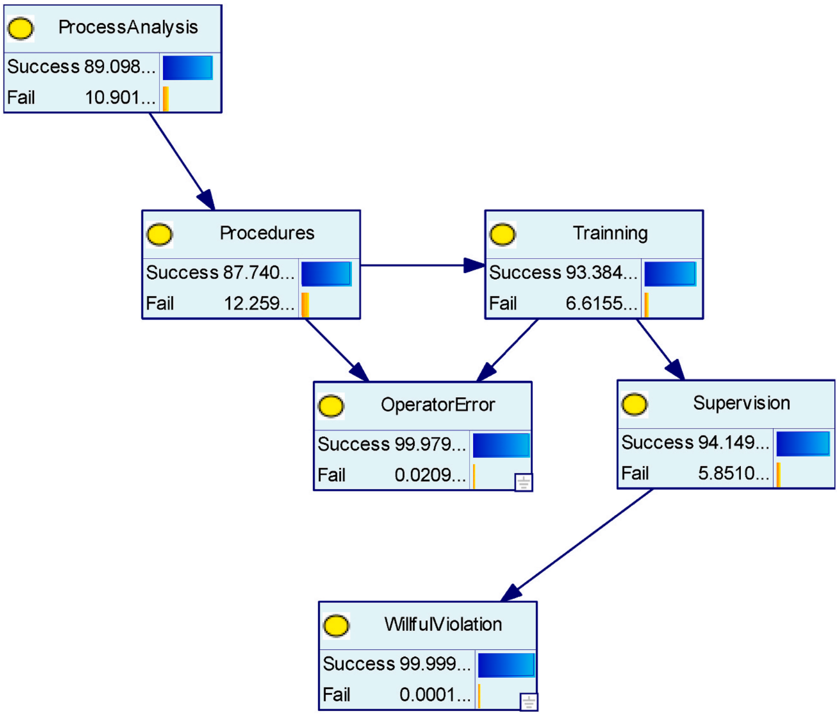


**Fig. 9.** The kernel Bayesian network with virtual evidence.

**Table 5**
The marginal probability of HEP on evidence of organizational factors.

| Organizational factor | State | P(H2=Fail) | P(H4=Fail) | HEP |
|---|---|---|---|---|
| Procedure | 0 | 1.29E-2 | 1E-4 | 1.3E-2 |
| | 1 | 7.82E-2 | 2E-4 | 7.84E-2 |
| Training | 0 | 1.46E-2 | 1E-4 | 1.47E-2 |
| | 1 | 1.10E-1 | 5E-4 | 1.11E-1 |
| Supervision | 0 | 1.92E-2 | 1E-4 | 1.93E-2 |
| | 1 | 4.86E-2 | 1.3E-3 | 4.99E-2 |
| Process analysis | 0 | 1.90E-2 | 1E-4 | 1.91E-2 |
| | 1 | 3.67E-2 | 2E-4 | 3.69E-2 |

## 5. Socio-technical system reliability estimation

### 5.1. System description

This case study was originally from a gas and oil plant that stores LPG in pressurized spherical tanks. A periodic non-destructive detection involving defects test of welding joints of a spherical storage tank was selected as a case study to apply the methodology. The sphere weld joints crack inspection with magnetic particles is a safety-significant process, with the components of workers (supervisor, technicians, operators), facilities (sander tools, scaffold), and their interaction. We selected polishing the welding joints process as a case to build the simulation scenario.

### 5.2. Task analysis

A reliability block diagram (RBD) is a standard method to quantify system reliability. Ahn, Kurt, & Akyuz [26] introduced humans into RBD as a component to describe human-machine interactive tasks. This research will adopt a similar approach. Then, the reliability of a series system of 'n' components with reliability $\mathbf{R} = \{R_1, \ldots, R_i, \ldots, R_n\}$, the series system reliability $R_s$ will be:

$$R_s = \prod_{1}^{n} R_i \tag{4}$$

The system reliability of a parallel system of 'n' components with reliability $\mathbf{R} = \{R_1, \ldots, R_i, \ldots, R_n\}$, the parallel system reliability $R_p$

will be:

$$R_p = 1 - \prod_{1}^{n} (1 - R_i) \tag{5}$$

Particularly, for modeling human and machine interaction, if the activity is performed by humans using the machine, the relationship will be calculated as a series of system components. On the other hand, if a human performs the activity and checks the machine, the relationship will be calculated as parallel system components. The sensitivity of the system reliability will be calculated as the derivative of the changing range of system reliability for the changing range of influential parameters.

The polishing of welding joints includes five sequential tasks, as Table 6 shows. In step 1, the supervisor checks the sander tools. In step 2, the crew climbs up the scaffold sequentially. In step 3, the testing work group performs the polish work; the operator polishes, the technician checks, and the supervisor supervises the work. In step 4, the testing workgroup climbs down the scaffold. In step 5, the operator and technician clean the tank and mutually check the work. The resulting reliability block diagram is shown in Fig. 10.

### 5.3. Simulation

The simulation tool of Anylogic® was selected to simulate this system to quantify the system's reliability dynamically. A combination of agent-based and discrete process simulation methods is employed. In the real process maintenance and testing working scenario, workers rarely work alone but in a team with different roles. To represent these human components in the system, we build the agent testing workers with roles of supervisor, technician, and operator. At the same time, we introduced the facility resource agent to represent the working instruments, such as a sander and scaffold, and their failure rate. In this case, to focus on human factors, the equipment and tools are supposed to have a failure rate of 0.001 [27]. According to the Bayesian network shown in Fig. 9, the human failure rate gets the max value of 0.14 as the procedure, training, and supervision factors are all in the failure state. In contrast, the human failure rate gets a minimum value of 0.01. In addition, Table 5 shows the mode value of the human failure rate under a different scenario.

The human failure rate could be generated randomly from a triangle distribution, which is mostly employed when the min, max, and mode values are available but not the precise distribution.

The polish process for supervisors, technicians, and operators, including checking the sander tools, climbing up the scaffold, polishing and climbing down the scaffold, and cleaning, the discrete events model is built as Fig. 11 shows.

### 5.4. System reliability sensitivity analysis

In this section, a sensitivity analysis is performed to investigate the effects of critical MOFs on the failure processes of the human-machine interaction system. The states of the five influencing organizational variables are set to 0 or 1, then the model simulates the random process to calculate the change rate of system reliability. The violin plot Fig. 12 compares the different distributions of the organizational factors with the state as success or failure. Based on the Mann-Whitney $U$ test, we can be 95 % confident that the true effect size of the training factors lies between 0.82 and 0.83. While the true effect size of the procedure factors lies between 0.65 and 0.68.

## 6. Discussions and implications

The proposed methodology advances compared to the state-of-the-art, including a proper data source chosen strategy, accident report database with high-quality and CBN learning techniques, which could reduce subjective bias and save model-building time. The resulting model is validated by its error prediction ability and sensitivity analysis.

This research employed a BN learning algorithm to consider causality analysis with tests of confounders, not just correlation analysis. Liu et al. (2022) presented the clusters of factors influencing human failure [13]. This research digs deeper into the quantitative dependencies and interaction of the organizational factors that contribute to human failure. In this way, machine learning can explore the causal relationship between factors.

Based on the Bayesian network learned from accident report data, training and procedure are the most critical organizational factors influencing human failure. It is an essential and general method to enhance human reliability by continuously improving the procedure and training program. Interestingly, the human failure mode of willful violation is significantly impacted by direct

**Table 6**
Task analysis of the polish process.

| Step | | Human | | | Machine | Interaction |
|---|---|---|---|---|---|---|
| NO. | Description | supervisor | Technician | operator | | |
| 1 | Check tools | 1 | 0 | 0 | Sander tools | Check |
| 2 | Climb up | 1 | 1 | 1 | Scaffold | Use |
| 3 | Polish | 1 | 1 | 1 | Sander tools | Use |
| 4 | Climb down | 1 | 1 | 1 | Scaffold | Use |
| 5 | Clean | 0 | 1 | 1 | | |

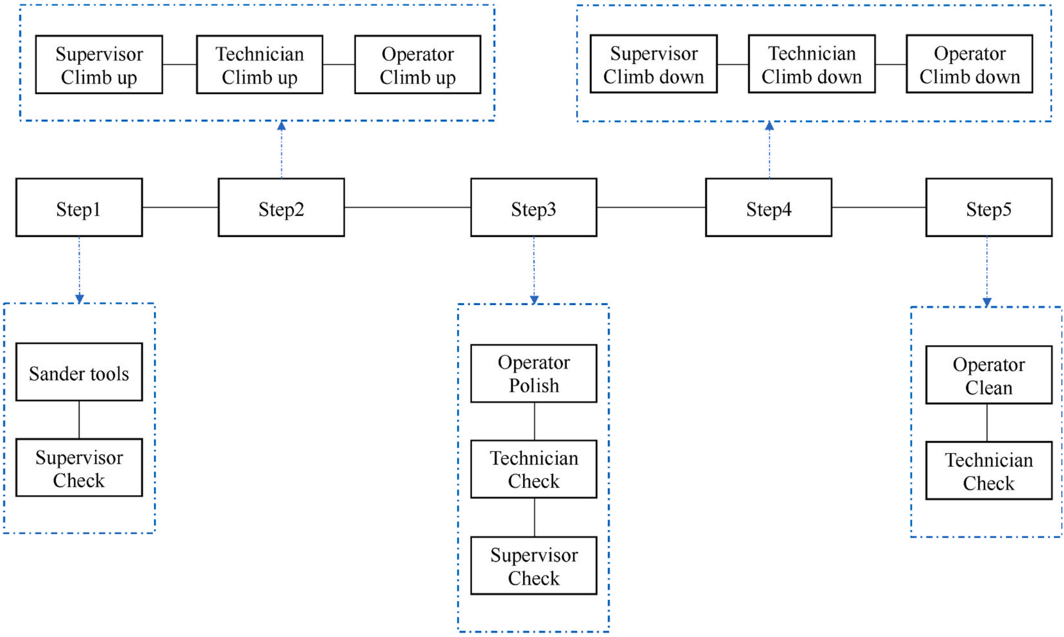


**Fig. 10.** Reliability block diagram of a Polish process.

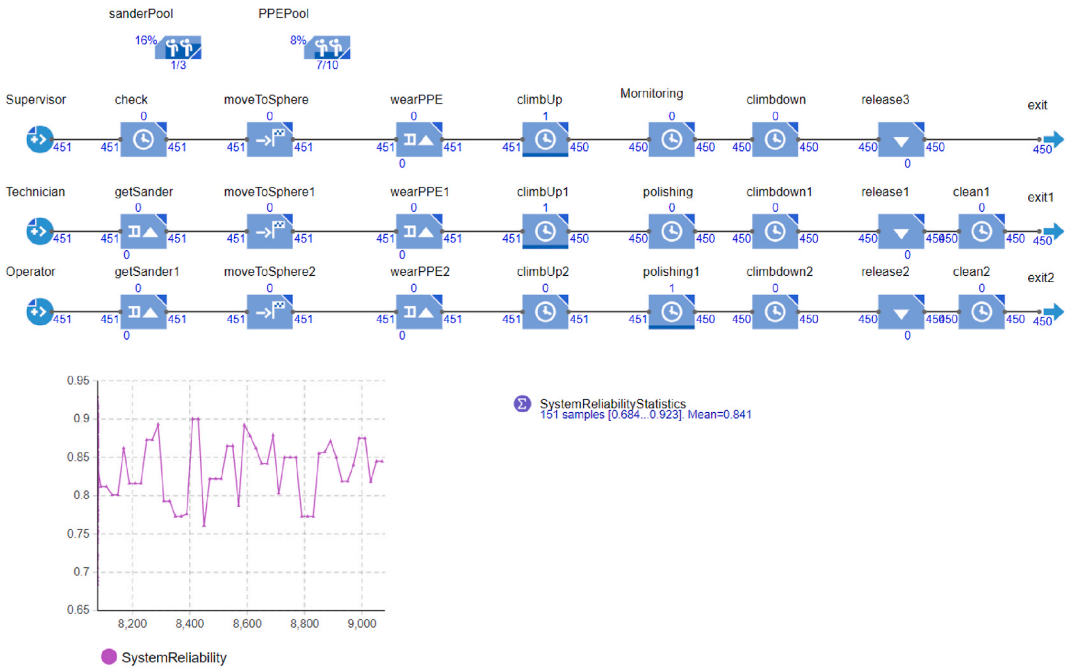


**Fig. 11.** Simulation of the polishing scenarios.

supervision. Despite this initial attempt, this Bayesian network is not a complete and complex one since this research aims at developing a data-driven methodology and core robust kernel Bayesian network. It could be a solid foundation and the starting point for later research.

It can be seen from the CBN that the Operator Error probability value was initially higher than the general normal value, like the HEP in THERP or CREAM, about 0.001. The reason is that the dataset came from accident reports, which means the data was conditional, and all the cases were in the context of accidents or some near-miss cases. So, the Bayesian update utilizing the soft evidence technique was employed and based on the nominal value of the literature from SPAR-H. Then, the scaler of the HEP from the Bayesian

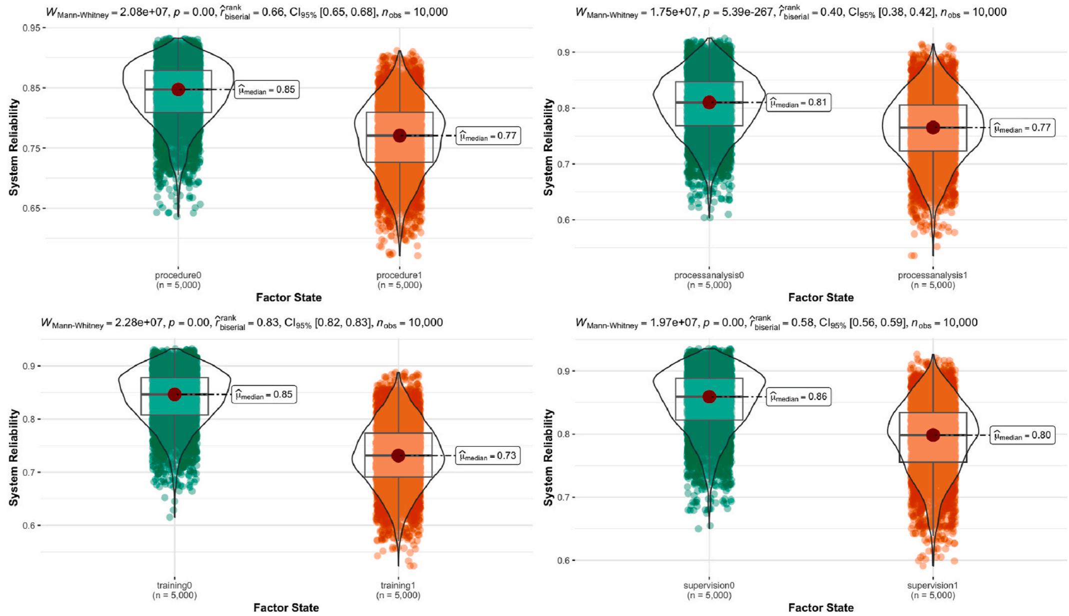


**Fig. 12.** System reliability sensitivity to organizational factors.

network can be acceptable. In addition, the focus of this research is not to calculate the HEP but to seek the causality mechanism of organizational factors to human reliability. Therefore, the absolute value of the HEP does not matter too much in the propagation of the influencing strength of organizational factors to the system's reliability.

Utilizing the learned CBN, the ranges of human failure rates when the controlled influencing factor is set to success or failure. A simulation model was built to calculate the reliability of the human-machine interaction system. The workers and facilities were represented as agents with their failure rates. The operator's failure rate was selected randomly from the range. As shown in 5000 simulation scenarios, the system reliability significantly differs as the controlled variable changes. The reliability of the human-machine interaction system is sensitive to critical organizational factors like training and procedure.

## 7. Conclusion

Based on the eMARS dataset, data from 40 years from 1980 to 2022, up to 893 accident cases are extracted and factorized. This study uses a data-driven approach and hybrid algorithms to investigate the organizational factors influencing human failure. The data-driven approach could reduce subjective bias. The bootstrap samples technique was employed to optimize the robust CBN structure.

Although this CBN structure only involves five organizational factors, it could not be a complete set of all the influencing organizational factors. As a stable attribute of CBN, this CBN can be the kernel of the more comprehensive PSFs Bayesian Network to support structure learning when more specific data is available. The case study validated that the proposed CBN can be utilized to calculate the range of human error rate, which could be used to simulate the human-machine interaction system reliability. The simulation scenarios show that the human-machine interaction system reliability is sensitive to the change of four organizational factors. The data shows that training and procedures contribute to the system's reliability the most. This validates the theory that organizational factors can influence system reliability by contributing to the human error rate.

The limitation of this study is the probability calculation based on the accident reports data, which is undetailed, especially for the human cognitive function analysis part, nearly no data about that area. Therefore, future work is needed to employ the field investigation or experiment approach to explore the human cognitive function factors contribution to the HRA.

## Data availability statement

The data that support the findings of this study are openly available in Causal Factors Coded from eMARS Dataset at http://doi.org/10.17632/6m82rtk89vw.1 reference number [reference number].

## CRediT authorship contribution statement

**Shuo Yang:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Micaela Demichela:** Writing – review & editing, Supervision, Resources, Project administration. **Jie Geng:** Validation, Investigation, Data curation, Conceptualization. **Ling Wang:** Supervision, Resources. **Zhangwei Ling:** Validation, Investigation.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shuo yang reports financial support was provided by China Scholarship Council. Shuo yang reports a relationship with China Scholarship Council that includes funding grants.

## Acknowledgments

The work is supported by the China Scholarship Council.

The models described in this paper were created using the GeNIe Modeler, available free of charge for academic research and teaching use from BayesFusion, LLC, https://www.bayesfusion.com/.

## Annex A.

**Table A.1**
Definition of organizational factors in literature.

| Factors in EMARS | Synonyms | Description | Literature source |
|---|---|---|---|
| Design of plant/ equipment/system | Design | • Ergonomically poor design of tools or equipment | [28] |
| | Design | • Technical design of plant and hardware and its safe modification to provide optimal safety | [29] |
| | Plant design | • When selecting suitable equipment, consider:<br>■ standards and codes;<br>■ compatibility of materials with products;<br>■ anticipated duty and degradation methods;<br>■ pressure systems;<br>■ life expectancy;<br>■ electrical integrity and equipment bonding; and<br>■ ease of inspection and maintenance. | [30] |
| | design | • refers to the physical construction and assembly of process- and other equipment. The design must be such that the installation can be operated and maintained without causing leaks. | [31] |
| Maintenance/repair | Maintenance | • no or inadequate performance of maintenance tasks and repairs, bad planning | [28] |
| | Inspection and maintenance | • The specification of scope and frequency of the inspection and maintenance system. This should be based on how safety-critical the item is, and on the degree of the challenge presented to the system integrity, or to comply with instructions from manufacturer or supplier.<br>• Safety-critical plant and equipment (ie flexi hoses, couplings, pumps valves, flanges, fixed pipes, bulk tanks) are inspected for wear and damage or malfunction within the specified period.<br>• Faults are fixed within specified timescales and repairs and improvements meet plant design standards.<br>• A log of findings kept – enabling trending. | [30] |
| Management attitude problem | Organizational Climate | Refers to the working atmosphere within the organization (e.g., structure, policies, culture) | [32] |
| | Top management culture | • system to manage conflicts between safety and other company goals explicitly, for example, in production and maintenance planning, purchasing, design, and so forth | [29] |
| | Safety culture | • characterizes the organizational attitude, values, and beliefs toward worker and public safety | [33] |
| Management organization inadequate | Adequate organization | • shortcomings in the organizational structure, organization's philosophy, management strategies | [28] |
| | Adequate organization | • The quality of the roles and responsibilities of team members, additional support, communication systems, Safety Management System, instructions and guidelines for externally oriented activities, the role of external agencies, etc. | [34] |
| Organized procedures | Procedures | • insufficient quality or availability of procedures, manuals and written instructions | [28] |
| | procedures, goals, plans, and rules | • specifying what to achieve in safety, and/or how to achieve it | [29] |
| | Operation procedures | • Procedures contain correct scope (key actions and tasks including emergency action) and/or sufficient detail.<br>• Procedures are clearly written/easily understood.<br>• Procedures are kept up to date. | [30] |

(continued on next page)

**Table A.1** (*continued*)

| Factors in EMARS | Synonyms | Description | Literature source |
|---|---|---|---|
| | Procedures, JSA, guidelines, instructions | • refers to all written and oral information describing how to perform the operational and maintenance tasks in a correct and safe manner. The main emphasize is on the task information necessary to avoid the occurrence of leaks. | [31] |
| | Procedures and document | • the written remedies and illustrations that describe operational/maintenance routines and plant/installation design/status | [35] |
| | | • Procedures are explicit, step-by-step instructions for performing a task. | [33] |
| | | • Guidance, and Instructions, This PIF refers to the availability and usefulness of operating procedures, guidance, and instructions (including protocols). Procedures, guidance, and instructions (PGIs) should be validated for their applicability and usefulness. Following PGIs should lead to the success of important human actions. | [5] |
| | | • Formal written guidance (including maintenance manuals, surveillance procedures, operating procedures, and emergency operating procedures) provided to workers or supervisors | [36] |
| | Availability of procedures/ plans | • Procedures and plans include operating and emergency procedures, familiar patterns of response heuristics, routines, etc. Procedures and plans include operating and emergency procedures, familiar patterns of response heuristics, routines, etc. | [34] |
| | | • refer to the availability and quality of the explicit step-by-step instructions needed by the crew to perform a task. Ideally, no errors should be committed by the crew when they are following the procedure correctly. However, procedures could be written incorrectly and therefore lead the crew to make errors even with the right intent. This group is made up of two level 2 PIFs namely: Procedure Quality and Procedure Availability. | [37] |
| Staffing | Staff competence | • Information and training covering:<br>■ hazardous properties of products;<br>■ ship-to-shore communication systems;<br>■ pre-transfer checks;<br>■ product transfer controls and monitoring;<br>■ post-transfer checks;<br>■ emergency actions.<br>• Job-specific knowledge and relevant experience of:<br>■ substances;<br>■ work processes;<br>■ hazards; and<br>■ emergency actions | [30] |
| | One element of management | • refers to the way that the organization hires and assigns tasks to personnel | [33] |
| | staffs | • refers to having adequate, qualified personnel to perform the required tasks. Staffing includes the number of personnel, their skill sets, job qualifications, and staffing structure (individual and team roles and responsibilities). Adequate and qualified staff is normally expected. | [5] |
| | Manning parameters | • refer to how many and what kinds of people perform which types of jobs. | [4] |
| | Resource Management | • Refers to the organizational-level decision-making regarding the allocation and maintenance of organizational assets (e.g., human resources, monetary/budget resources, equipment/facility recourse). Organizational Climate: Refers to the working atmosphere within the organization (e.g., structure, policies, culture). Operational Process: Refers to organizational decisions and rules that govern the everyday activities within an organization (e.g., operations, procedures, oversight). | [32] |
| Training/instruction | Training | • inadequate planning, ineffectiveness of trainings, insufficient competence or experience of personnel | [28] |
| | Training | • refers to the knowledge and experience imparted to the personnel by the utility. Training includes the content of training courses, the scheduling of training courses, and the frequency of training. | [33] |
| | Training | • refers to training that personnel receive to perform their tasks. Included in this consideration are personnel's work-related experience and whether they have been trained on the type of the event, the amount of time passed since training and training on the specific systems involved in the event. It is expected that adequate training is required for professional staff. | [5] |
| | Training | • review training documentation and train records to assess the adequacy of the training program for the tasks related to the event.<br>• Interview training department personnel. Discuss specific problems with worker/supervisor knowledge and skill identified during interviews with workers and supervisors. | [36] |
| | Adequacy of training and experience | • The level and quality of training provided to operators as familiarization with new technology, refreshing old skills, etc. It also refers to the level of operational experience. | [34] |

(continued on next page)

**Table A.1** (*continued*)

| Factors in EMARS | Synonyms | Description | Literature source |
|---|---|---|---|
| | Training/competence | • refers to the training and competence that is necessary for the operating personnel to carry out their jobs without causing any leaks. This covers both general system knowledge and specific skills required for operational and maintenance tasks | [31] |
| Direct Supervision | Direct supervision | • Direct supervision serves as the link between management and the team members. The direct supervisor can be seen as a member of the team, albeit a member with additional authority and responsibility. | [33] |
| | supervision | • First or second-line managers of production/maintenance works, including preparation and supervision during work. | [36] |
| User-unfriendliness (apparatus, system, etc.) | User-unfriendliness | • A user-friendly and ergonomically responsible interface in all life-cycle phases | [29] |
| | HIS | • The Human-System Interface PSF covers how information is communicated between humans and machines. | [33] |
| | HMI | • refers to indications (e.g., displays, indicators, labels) and controls used by personnel to execute actions on systems | [5] |
| | HSI | • refers to the ways and means of interaction between the crew and the system. This PIF covers the quality (usability, ergonomics, physical access, etc.) of the HSI both in terms of system output as well as the crew's input to the system. | [37] |
| | Adequacy of MMI and operational support | • The Man-Machine Interface in general, including the information available on control panels, computerized workstations, and operational support provided by specifically designed decision aids. | [34] |
| | Human engineering | • Criteria that support reliable human performance and will result in people doing tasks in a consistently correct manner.<br>• Including human-machine interface, labels less than adequate, arrangement/placement, instrument/displays less then adequate, controls less than adequate, monitoring alertness less than adequate, unit differences | [36] |

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